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CREATION OF OPTIMAL PRODUCT FAMILIES TO ACCOMMODATE HUMAN VARIABILITY USING PRINCIPAL COMPONENTS ANALYSIS

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ABSTRACT

The objective of this thesis research is to develop a method based on principal components analysis (PCA) to create optimal product families of artifacts, tasks, or environments intended for human use. This study formulates a procedure to estimate the levels of commonality and distinctiveness required in a product family designed to accommodate human variability. Families of products that users physically interact with are considered in this thesis with the aim of maximizing the accommodation (a product which fits the users is said to "accommodate" the user) afforded by these products. The multivariate statistical technique of PCA is employed to assess the anthropometric variability in the target user population. The usual methods of improving the accommodation of a product are: a) incorporating adjustability and b) scaling (offering different sizes). Different sizes can be considered a product family. Among the various components in the products of the family, some will be similar and others will be distinct. The manufacturing costs can be reduced, and the profits can be increased, if the commonality and distinctiveness are optimized such that accommodation is maximized. Since the products are intended for human use, accommodation will be governed by human variability, particularly anthropometry. PCA is used to identify the underlying pattern in human variability so that the relative proportions of scaling and adjustability can be assessed and assigned appropriately to the products in the family. Three case studies are used to demonstrate the proposed method.

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CHAPTER 1

INTRODUCTION

The objective of this thesis research is to develop a method based on principal components analysis (PCA) to create optimal product families of artifacts, tasks, or environments intended for human use. This work will be beneficial for designers and users since these product families will: a) maximize the accommodation offered by the product, thereby increasing the number of potential users, and b) reduce time and cost needed to develop the offered variants.

Products intended for human use have to be designed to accommodate (i.e., satisfy certain performance objectives: comfort, safety, visibility, ease of use, etc.) their target user populations. For example, in order to allow the desired percentage (say 95%) of the target users to enter a building without having to bend over, the height of the door should be at least equal to the 95th percentile height of the target population. This requires studying the variation in the stature of the users of the door. Similarly, relevant body dimensions (anthropometry) have to be studied to enable the design of other products.

Each individual user interacts with a given product in their own way. For example, no two people are likely to sit in a chair in the same way. This can be attributed to the various sources of human variability. *Design for Human Variability* (DfHV) looks to account for these forms of variability in designing products for target user populations. DfHV considers several kinds of variability amongst users and studies their effects on design outcomes like fit, comfort, and safety. The kinds of variability amongst humans are differences in body size and shape; capabilities owing to age, gender, physical, and mental health; usage owing to culture, economy, ethnicity, etc. An additional factor to be considered while designing is preference, which describes how two ostensibly similar users will interact with an artifact in different ways. Therefore, a designer has to consider the variability amongst the consumers and their preferences to ensure the success of a product. Typically, a product is offered in different sizes and/or adjustability is allocated within a size to achieve the decided level of accommodation [17]. A certain accommodation level is decided upon, and product specifications are subsequently determined to achieve this accommodation level at minimal cost to the manufacturer.

While designing a product with which users physically interact, DfHV techniques take into account the anthropometry of the target user population to predict the human variability. Stature and BMI of the target user population are the most commonly used predictors [18] since stature can be measured easily and BMI can be readily calculated if the corresponding stature and weight are known. The problem could be described as univariate, bivariate, or multivariate based on the number of variables that have to be considered. As the number of variables to be considered increases, univariate analyses fail to achieve the required level of accommodation [31]. Human variability cannot be predicted with complete accuracy if just two predictors (for example, stature and BMI) are used. In general these problems are mitigated by the simultaneous consideration of multiple variables or by considering residual variance of the regression [32].

Another way to overcome this road-block is through the use of *principal components analysis* (PCA) [12, 11, 24]. PCA identifies the direction of maximum variance amongst a set of dimensions. It can be used to identify the underlying basis of variability within the anthropometric factors considered [25]. PCA re-expresses data along new orthonormal bases. The first few principal components capture the maximum variability if the data are highly correlated; these principal components are used to interpret the data.

A traditional method of using PCA in design has involved the generation of families of manikins [12, 11, 22, 24] that are representative of the variation of anthropometry within target populations; a design is considered to accommodate the target population if it fits every manikin in the family. In contrast to this approach, this work explores the utilization of PCA to concurrently solve the DfHV and product family design problems.

Product families can be an important strategy for companies to be able to offer the required amount of variety in product lines while controlling resource requirements (money, time, material, and manpower). The demanding market dictates that companies offer many alternatives of a product. To maintain profitability, companies may need to offer product variety without incurring heavy costs or investing large amounts of time in product development. Many goods like vehicles, electronics, appliances, clothing, etc., are offered in a wide variety in order to cater to consumer's varying tastes and sizes. Designing product families enables companies to provide larger amount of variety for the market while keeping the variety within products as low as possible. It utilizes the concepts of commonality, modularization, and standardization to optimally create new products [41]. The common components in the variants of a product are identified and grouped together. These components constitute the product platform. The parts of a platform can then be scaled and assembled in various ways to yield numerous different products [26].

The primary contribution of this work is the use of the multivariate statistical technique principal components analysis to interpret and assess human variability and to accordingly divide the target population into product family groups. This allows for the development of product families to address the variability within each of these groups and thereby increases the accommodation level of the target population. The data interpretation based on PCA simplifies the multivariate problem. It also offers insights into other design decisions, such as those regarding incorporation of adjustability and sizing into the design.

The principal components consist of various combinations of anthropometric measures. These anthropometric measures are directly related to the design parameters. The manner in which the anthropometric measurements influence these principal components helps to decide which parameters should be sized or made adjustable. These decisions can govern the sizing of specific components in the product family. The components with the same dimensions are identified and grouped together to constitute the product platform. The product family is thereby able to maximize the accommodation, and the product platform helps in minimizing development time and cost. Therefore, the method proposed in this thesis can help increase the profitability of the design.

The next chapter presents concepts related to product family design including: commonality, distinctiveness, product platforms, and the domain mapping matrix. It also provides an explanation of PCA with the help of two examples. It reviews existing studies that employ PCA to solve problems involving designing for human variability. A method is proposed in Chapter 3 that attempts to create optimal families of products intended for human use. Chapters 4-6 offer three case studies to illustrate the proposed method. The products considered in these case studies are: stools, chairs, and scooters. The final chapters discusses the contributions and limitations of this work.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1 Product family design

A product family is a group of related products that is derived from a product platform to satisfy a variety of market niches [41]. Each of these products caters to a segment of users, thus increasing the size of the overall target population of the family of products. The main advantage of product families is that they help companies offer a variety of products for the market without compromising on manufacturing efficiency (in terms of costs associated with product development or production). This is achieved by minimizing the variation within the product components. The components common across all the products in a product family are referred to as the product platform [41, 47, 30]. Companies can satisfy their customers' demands without developing new products from scratch with the help of product-platforming. For example, a person who wants to buy a car might want a 'sports engine' in a luxury car. A company that makes both sports cars and luxury cars might be able to satisfy this customer's demand if it uses the same platform for both cars. Minimal redesign or change to the assembly line will not be necessary in that case. Product families makes the offering of variants easier for a company.

The amount of similarity across the various products in a product family is termed commonality, and the differences are referred to as distinctiveness. The success of a product family depends on how well the trade-off between commonality and distinctiveness is resolved [47, 46, 28, 45]. Improving the economies of scale is one of the biggest advantages of commonality. In order to increase commonality, many manufacturers eliminate the non-value adding variants of the product [7, 26, 30].

The manufacturers make each product within a family distinct in ways the customers notice and identical in ways the customers might not be aware of [41]. For example, the functions performed by different products in a family and their user interface can be made different, but their internal components, which are hidden from the customer, can be made as similar as possible. More commonality reduces the cost of product development, but it can also reduce market appeal [42, 45]. Work by Thevenot and Simpson [46] proposes metrics to assess the degree of commonality in a product platform; these metrics help companies to make trade-off decisions. The metrics are called commonality indices and are based on factors such as the number of common components, costs, etc. In most cases, these metrics are calculated after product dissection and are very helpful in the redesign of products, and can also be the starting points for designing new product families [42, 48, 7].

Many companies (e.g., Black & Decker [30], Sony [39], and Ford Motor Vehicles [8]) have benefitted from product families. Modularity, standardization, and scaling are the tools used to optimize the product family design. Hewlett Packard [16] and Boeing [38] are some companies that have embraced the module-based and scale-based product family concept successfully.

Domain mapping matrix

An intuitive tool in designing product families is the domain mapping matrix (DMM). Domain mapping matrices are extensions of design structure matrices [5]. They are rectangular matrices that focus on the dynamics of product development and represent the dependencies between different domains [13].

A modified version of the product specification vs. product architecture DMM is utilized in this work to establish relations between components and final products. The two concerned domains are components and the size of the variant. DMMs can aid in visualizing the common components across different variants of a product. Therefore, they allow for traceability of the constants across the domains. This matrix helps in highlighting the common components and their dependence on each other across the whole family of products. Once the common components are identified, they can be grouped together to constitute a product platform. A detailed explanation of DMMs is provided in [15].

2.2 Explanation of principal components analysis

Principal components analysis is an effective technique to reduce the dimensionality of correlated datasets. PCA concentrates on variances [25]; it identifies patterns in the data [43] and re-expresses the variation in the given data with a set of orthonormal axes called Principal Components (PC). The maximum variance of the data lies along these axes. When ordered by variance, the first PC represents the direction with the highest variance. The second PC represents a direction perpendicular to the first PC with the next highest amount of variance, and so on. To achieve data compression, the first few PCs can be selected to solve the problem. Although the reduced data does not explain 100% of the variability present in the data, the compression simplifies the problem substantially [25]. This is why designers might prefer using PCA over retaining 100% of the variability in the data. PCA clears up the confusion in noisy data and sometimes helps to reveal a simple underlying structure which explains the variability better [40].

The definitions of some statistical and matrix algebra-related terms [43] are explained in the following paragraphs to help facilitate the understanding of principal components analysis.

The mean of a data set is a measure of the average value of elements in the data set. It is denoted by μ or by $\bar{x}$:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{2.1}$$

where n is the number of elements in the dataset. The first element in the dataset is denoted by x_1, the second element is denoted by x_2, and the i^{th} element is denoted by x_i. The standard deviation is denoted by s, and the variance is denoted by s^2. These are measures of the variability (spread or scatter) of a data set.

$$s = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n-1}} \tag{2.2}$$

If the data set is multi-dimensional, then covariance is calculated to assess the relationship between any two dimensions of the data set. If the covariance between two dimensions has a positive value, then the increase in value of one dimension implies an increase in the value of the other dimension. On the other hand, a negative covariance between two dimensions implies that if the value of one of the dimensions increases, the value of the other is likely to decrease. If the covariance is zero, then the two dimensions are independent of each other; changes in either dimension will not have a consistent impact on the other dimension. Let one dimension of the dataset be denoted by a and an other dimension be denoted by b; then covariance between a and b can be calculated as:

$$cov(a,b) = \frac{\sum_{i=1}^{n} (a_i - \bar{a}) \times (b_i - \bar{b})}{n-1} \tag{2.3}$$

Let **X** be an $m \times n$ matrix representing the data. Here, n signifies the number of variables for each of the m individuals in the matrix. For PCA to work properly, **X** should be centered, which is done by subtracting the mean value of the dimension concerned for each individual [43, 35] (an example is included in the Section 2.2.1 to demonstrate the procedure). Let the centered **X** be denoted by **Y**. The covariance matrix (COV) (which is an $n \times n$ matrix) of the n columns of the **Y** matrix is calculated. The eigenvalues and eigenvectors are calculated based on COV. The eigenvectors are then ordered corresponding to the eigenvalues, highest to lowest. A matrix **P** is obtained by selecting the first p eigenvectors (p depends upon the amount of variability needed to be considered to solve the problem) ordered by eigenvalue. This facilitates data compression. **P** is the matrix of selected eigenvectors. **Y** is the centered **X** matrix. **C** is the product of the transpose of matrices **P** and **Y** [43, 40, 25, 35].

$$\mathbf{C} = \mathbf{P^T} \times \mathbf{Y^T} \tag{2.4}$$

Statistical and mathematical software like **R** and **MATLAB** have functions to perform PCA and hence make the computation and application of PCA fairly starightforward.

PCA can also be based on the correlation coefficient matrix instead of the covariance matrix. The covariance matrix only characterizes uniform variation whereas the correlation matrix characterizes the variability resulting due to combinations as well (small torsos with long limbs etc.) [24].

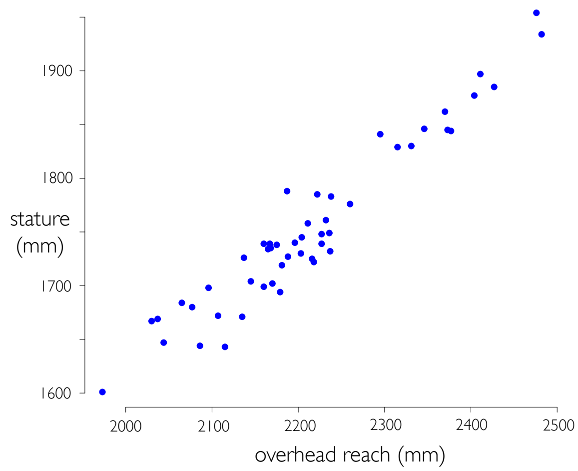
2.2.1 Examples

The following examples make the usefulness of principal components more clear. The data in Figure 2.1a show the correlation between two anthropometric variables: (1) overhead reach and (2) stature. The plot has 50 observations selected from the ANSUR database [21]. The horizontal axis corresponds to overhead reach, and the vertical axis corresponds to stature. The minimum value corresponding to stature is 1600 mm, and the maximum is 2000 mm. For overhead reach these values are 1980 mm and 2500 mm, respectively. It can be seen that stature and overhead reach are correlated.

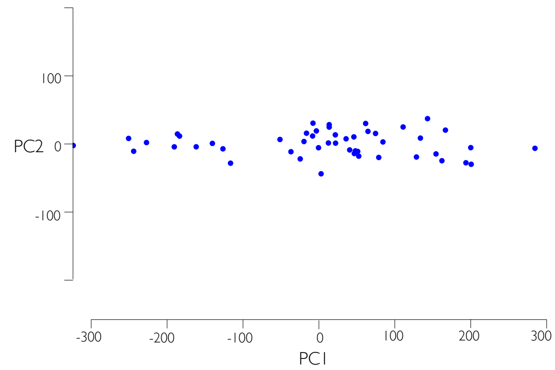
Figure 2.1b shows the plot of the same 50 observations transformed to the PC axes. As expected, the variation along the direction of first principal component is much greater than the variation in the y-axis. The first principal component is the direction of maximum variability in the data. The second principal component is the direction with the next highest amount of variability, perpendicular and therefore totally uncorrelated to the first principal component direction. If the original variables are highly correlated, then the initial principal components explain most of the variability contained in the data and the last few principal components contain very little variation. Although Figure 2.1b clearly shows that variation along PC1 is much greater than the variation along PC2, the reduction in the complexity of the problem is exemplified better when the number of original variables is large.

PCA points out the direction of maximum variability and also compresses the dimensionality of the data. The first few PCs have the capability of explaining the majority of the variability in the data [49]. This can be illustrated by the following example.

Ten measures were extracted from the ANSUR [21] database. The variables and their corresponding contribution to the overall variance in the data are listed in the Table 2.1. The percentage of variance for each measure was obtained by dividing its variance by the sum of variances of all the measures. Measures such as overhead reach, stature, chest height, etc., that correspond to length seem to be responsible for most of the variability in the data, whereas measures corresponding to breadth contribute significantly less to the



(a) Correlation between overhead reach and stature of 50 subjects extracted from the ANSUR database [21].



(b) Plot of the 50 observations extracted from the ANSUR database [21] with respect to their principal components PC1 and PC2.

Figure 2.1: Plots demonstrating the transformation of the anthropometric variables to the principal components space.

variability in the data. Principal components are obtained after applying PCA to these ten measures. Each principal component and the percentage of variability it represents are listed in Table 2.2. Table 2.2 shows that the first three principal components contain 95% of the variance in the data; the rest of the principal components account for only 5% of the variability and have therefore been grouped together. Figure 2.2 accompanies these tables for the ease of visualization. These tables and figures show that in order to include 95% of the variability, eight anthropometric variables have to be considered; however, if the same problem is solved using the PC space, only 3 principal components have to be considered. This example shows that PCA can be used to reduce an eight-dimensional problem to a three-dimensional problem, often simplifying a design problem.

2.2.2 Application of PCA in DfHV

General background

PCA has been applied in various ways in designing for human variability. Traditional approaches have used PCA to identify a set of boundary manikins [24, 29] or to generate families of manikins [12, 11]. Recent work [9, 34] have used the technique to create virtual populations and aid in virtual fitting trials. This thesis uses PCA to change the basis from the original anthropometric variables to the orthonormal PCs, which are of reduced dimensionality and are therefore easier to use. The physical significance of the PCs is interpreted with the help of the factor loadings of the variables.

Moroney and Smith [31] emphasize the need for applying a multivariate analysis technique like PCA to a multivariate problem. Their study shows the lower-than-desired accommodation achieved as a result of using univariate analysis in a multivariate design problem. PCA is generally not the sole analysis applied to a design problem; the results of PCA are sometimes inputs to other multivariate analyses such as regression. PCA should be used only when the number of observations are at least five times greater than the number of variables [44, 31].

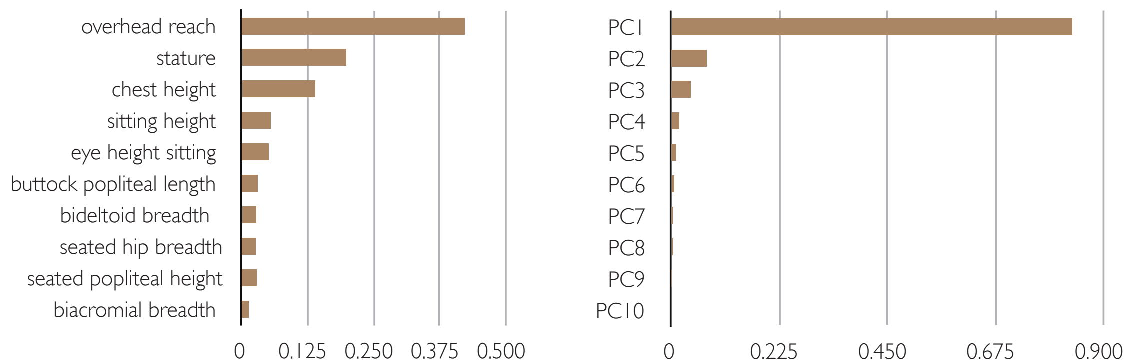
A-CADRE, the USAF multivariate accommodation method [24], also uses the technique developed by Bittner [12]. This study stresses the fact that PCA works well only

Table 2.1: Ten anthropometric variables and the percentage of variance in the data attributable to each variable. The ten variables explain 100% of the variance in the data, we need to consider eight variables to explain 95% of variance in the data.

Anthropometric Variable	Percentage of variance in the data
overhead reach	42.25
stature	19.82
chest height	13.96
sitting height	5.62
eye sitting height	5.19
buttock popliteal length	3.14
bideltoid breadth	2.81
seated hip breadth	2.75
seated popliteal height	2.98
biacromial breadth	1.43
Total	100%

Table 2.2: The principal components generated after applying PCA to the ten anthropometric variables and the percentage of variance attributable to each PC. Only 3 PCs have to be considered to explain 95% of the variance in the data.

Principal component #	Percentage of variance in the data
1	83.46
2	7.55
3	4.16
4-10	4.779
Total	100%



(a) Variability contained in the various anthropometric measures.

(b) Variability contained in the various principal components.

Figure 2.2: Bar charts to demonstrate the data compression that PCA achieves. Eight variables have to be considered in the anthropometric variable space to explain 95% of the variability in the data while the same amount of variability can be explained by considering the top 3 PCs only.

when the initial variables have good correlation. For example, if the body dimensions with poor correlation (for example, facial dimensions) are chosen, then the method will fail. This failure can be attributed to the fact that when the variables are poorly correlated to each other, the factor loadings of all variables will be comparable. Therefore, the first few PCs will be unable to explain high amounts of variance.

The Foot Anthropometry study in Hong Kong [19] determines an equation to explain the relationship between PCs and the initial variables. Most of the subsequent work [50, 22, 23] just interprets the PCs on the basis of the loadings of the various variables. Since this work only used thirty one subjects, it did not produce any results readily applicable to DfHV. The study proves the inadequacy of just one variable, foot length, as the basis for shoe sizing system; foot width and foot height are also shown to be required [19].

Traditional anthropometric techniques and 3D body scans were used to measure 103 variables in the research outlined in Zheng et al. [50]; PCA and K-means cluster analysis were successfully utilized to develop a new sizing system based on just three measures and their combinations. There were a total of 1115 participants in this study; the results obtained in their paper therefore promise to be readily applicable to DfHV problems. This work agrees with the idea mentioned in Goonetilleke et al. [19]: one or two variables are not sufficient to design clothes specifically manufactured for a body part with a complex geometry.

Certain DfHV problems, such as those involving the design of clothes, footwear, backrests of chairs, car compartments, etc. require more information than just anthropometric measures (heights, widths, weights, etc.). Such problems require information about the shape of human body. Some DfHV research has used PCA to extract information from whole body scans (CAESAR) and generate 3-D digital human models that provide useful information regarding the human body shape [9, 35].

Manikin approach

The PCA-based manikin approach differs from the traditional manikin approach; it recognizes that using a large or small person to validate the design does not always yield proper results. Some individuals can be 95th percentile by stature and a much smaller percentile for some other measure like width. The CADRE [12] and A-CADRE [11] are sets of 17 manikins created to validate redesigned cockpits. Unlike the traditional univariate approach wherein only the two extreme values of each measure are considered, these 17 manikins facilitate validation at several different percentile values for each measure and therefore capture the variation in the data better. Their utility was proven equivalent to a sample of 400 operators drawn randomly from a population of operators. Their method applies PCA to the original datasets, selects and plots the first few principal components, and thereby reduces the problem's dimensionality.

Regularly spaced points on the figure enclosing the PCA cloud are selected as sources of information for the generation of manikins which represent the population accommodated inside the boundary [24]. The size of the enclosing figure depends on the desired level of accommodation. The first step of the method is to identify 19 anthropometric variables relevant to workstation design to create the CADRE [12] or A-CADRE [11]. The correlations between these variables are estimated and are analyzed using PCA. The first four PCs explain 75% of the variability represented by all the 19 anthropometric variables. The first four principal components are therefore selected and used to create a four-dimensional ellipsoid. The centroid of the ellipsoid and 16 regularly spaced points on its boundary are selected to be representative of the population within the ellipsoid.

The USAF multivariate method, developed by Hudson et al. [24], uses PCA to reduce a six-dimensional problem to a two-dimensional problem. Eight representative manikins on the boundary of an ellipse are selected. It is shown in [24] that the multivariate PCA approach is better than using just the percentile or the regression approach since PCA takes care of the proportional variance along with uniform variance.

The CADRE and A-CADRE manikins were examined by Meunier [29], and some sources of error in the analysis were established. For example, PCA takes only the correlation of the variables into account; the selection of relevant variables is subjective since it depends on the experimenter. His work examines the trade-off between retaining maximum variability and maintaining simplicity. The study highlighted that if PCA is used as a stand-alone technique, it results in lower-than-expected accommodation, due to the exclusion zones in cases where the size of the enclosing figure is small. If the enclosing envelope is small, then it tends to exclude certain individuals in the target user population who might belong to a cluster farther away from the axes. These clusters are typically known as exclusion zones.

Creating virtual user populations

Gathering anthropometric data manually from a sample of the target population can be a costly, time-consuming, and tedious task. The impracticality of this process induces designers to use previously collected data which might not be truly representative of the target population at hand. This leads to unintentional disaccommodation. In Parkinson and Reed [34], PCA and linear regression were used to generate a virtual user population using available anthropometric databases and demographic information about the target user population. The demographic information from the target user population and basic anthropometric information from a recent database (e.g., NHANES [14]) is used to create a weighted virtual user population. Their method also takes into account the correlations and covariances between the anthropometric variables of interest, taken from a detailed database like ANSUR [21]. The estimates obtained with their approach are better than those obtained when a simple weighting procedure is applied. Linear regression is used to establish a relation between the principal component scores and the basic anthropometry. The inversion of the principal scores thus obtained results in the generation of detailed anthropometry. Residual variance of regression is incorporated using a stochastic component. This generates dissimilar anthropometric details for two individuals with same predictor anthropometry which would be expected in a real population. The method established in their work can be applied to create anthropometric details for different target user populations.

PCA to analyze human body shape

In the studies by Allen et al. [9] and Parkinson and Reed [36], information was extracted from whole body scans, and PCA was used to generate three-dimensional human models. These studies primarily facilitate virtual fitting trials, thereby eliminating the need for real fitting trials. Virtual fitting trials reduce the development time and cost and are hence advantageous to designers.

In the work by Allen et al. [9], information obtained by a full body scan is processed to create a model. This model can be edited to get a new individual in a similar pose. In order to capture the wide scope of variability in human body types, 250 scans of different body types were selected to create a basic framework. Their work suggests that PCA can be used to develop new random individuals. The method for this would involve matching newly scanned individuals to the prepared template. The centered matching matrix will yield principal vectors after PCA, and there will be a variance s^2 associated with each principal vector. These variances can generate entirely new virtual individuals.

Parkinson and Reed [35] is a natural extension of the work by Allen et al. [9]. They present a method that combines the techniques of PCA and multiple regression to create statistical models of three-dimensional torso shapes. The body scan data yield geometry vectors of 11076 elements each. Men and women are analyzed separately, since they have different geometries. The PCA algorithm developed by Turk and Pentland [49] is used to reduce the dimensionality of the problem from 11076 to 60 while still retaining 99% of the variability. The 60 PC vectors are then used to regenerate the geometry of any number of individuals using stature and BMI as the predictors. Their work shows how body scan data of a limited number of subjects can be used to generate a large virtual population which is particularly advantageous since gathering body scan data is very expensive. The fitting trials performed on a large, virtually created population produce more accurate results.

Hsiao et al. [23] used PCA to reduce a thirteen-dimensional problem to a three-dimensional problem. They also expressed the 3 new variables as linear functions of the original variables. Their study employed 100 individuals, 94 of whom were actual agriculture workers, and they took their 3D scans for good sampling. They reached the conclusion that PCA provides useful representative body models and is a useful tool. Another study [22] based on similar lines employed 72 males and 26 females. Their body size and shape was measured using a 3D scanner and other anthropometric devices. Again, PCA was used to come up with 15 representative body models which can be used to test harness designs. A recent study aimed at improving seatbelt safety for firefighters also used 3D scans and PCA [33].

2.2.3 Designing in principal components space

PCA is very widely applied in fields of image recognition [10], image processing, and animation [6]. PCA can identify the base shape or the similarity amongst all animations fed to the analysis. Therefore, the first PC turns out to be a very good approximation of the overall shape. The first PC is generally driven by many of the original factors and thus enables data compression. The quality of the animation regenerated can be improved if the number of PCs utilized is increased [6, 40]. Thanks mainly to its ability to compress the dimensionality of the problem at hand, PCA recognizes the optimal coordinate system for the data and reduces the hassles in the design process especially by compressing the dimensionality of the problem.

Fundamental concepts related to product family design and the statistical procedure of PCA were reviewed in the beginning of this chapter. This was followed by a couple of examples which demonstrated the ability of PCA to find the direction of maximum variance in the data set, and to reduce the dimensionality of the data set. The next section of the chapter dealt with the various ways in which PCA has been applied to DfHV problems. These included creating boundary manikins, families of manikins, virtual populations, and analyzing human body shape. Designing in PC space was also explored, mostly related to the realm of animation and image recognition. The next chapter focusses on developing a method that utilizes designing in the PC space to create optimal product families which in turn achieve the target level of accommodation. The subsequent chapters establish the utility of the proposed method with the help of three demonstration studies.

CHAPTER 3

METHOD

This thesis aims to maximize the accommodation that a product provides by creating product families, which offer optimal number of sizes and right amount of adjustability in the product variants. Principal components analysis is employed to determine the components of the product that need to be sized and those that need to be made adjustable. It also helps to determine the parts of the product that need both scaling and adjustability and the parts that need neither.

It can be impractical to provide a large range of adjustability to a single product so that it can accommodate all users. For example, shoes can not address the variability of the whole target population by providing adjustability. Although creation of different sizes to accommodate a large number of users with a wide range of anthropometry can sometimes be a viable option (e.g., shoes are offered in a large number of sizes to address the variability of the target user population). Therefore, typically in cases where a large amount of variability must be addressed, sizes are created; whereas, when the amount of variability to be addressed is low, adjustability is provided.

When PCA is applied to highly correlated data, typically the first PC has the largest variance, and the second PC has the next largest variance. Therefore, sizes can be created based on the first PC, since it coincides with the direction of maximum variability in the data. The second PC has less variance, and it is possible to allocate adjustability within the sizes of the product so that the variability contained in the second PC is accommodated.

Figure 3.1 shows the expected qualitative relationship between number of sizes and the local aspect ratio. The local aspect ratio is dependent on the total aspect ratio. The total aspect ratio estimates the ratio of the variance contained in PC1 to PC2. The variance contained in a PC can be approximated by the span of that PC. The span can be obtained by calculating the difference between maximum and minimum score of a PC. PCS_{max} is the maximum value attained by the PC and PCS_{min} is the minimum value of the PC score.

$$L_{PC} = PCS_{max} - PCS_{min} \tag{3.1}$$

The total aspect ratio, denoted by l_r, is the ratio of the span of PC1 to the span of PC2.

$$l_r = \frac{L_{PC1}}{L_{PC2}} \tag{3.2}$$

Dividing the total aspect ratio by the number of sizes provides the local aspect ratio. The local aspect ratio is denoted by l_{rj} as shown in the following equation:

$$l_{rj} = \frac{l_r}{j} \tag{3.3}$$

where j is the number of sizes created in a product family .

Figure 3.1 depicts the expected change in the relationship between the number of sizes and the local aspect ratio as the total aspect ratio varies. The shaded area represents the design scenarios that require the creation of unreasonably high number of sizes and hence are not viable. Figure 3.2a shows the case where PC1 and PC2 contain almost the same amount of variance ($l_r = 1$), adjustability will have to be provided in order to accommodate the variability in this design scenario. Figure 3.2b represents the case in which l_r is close to 5. In such cases, creation of multiple sizes without the allocation of adjustability might suffice and the required accommodation can be attained.

If the first two PCs do not explain 95% of the variability in the data, more PCs are selected and the measures that influence PCs with higher variance are scaled and those that influence PCs with lower variance are made adjustable. The method proposed to identify components of a product platform when designing products for humans is described in the next section.

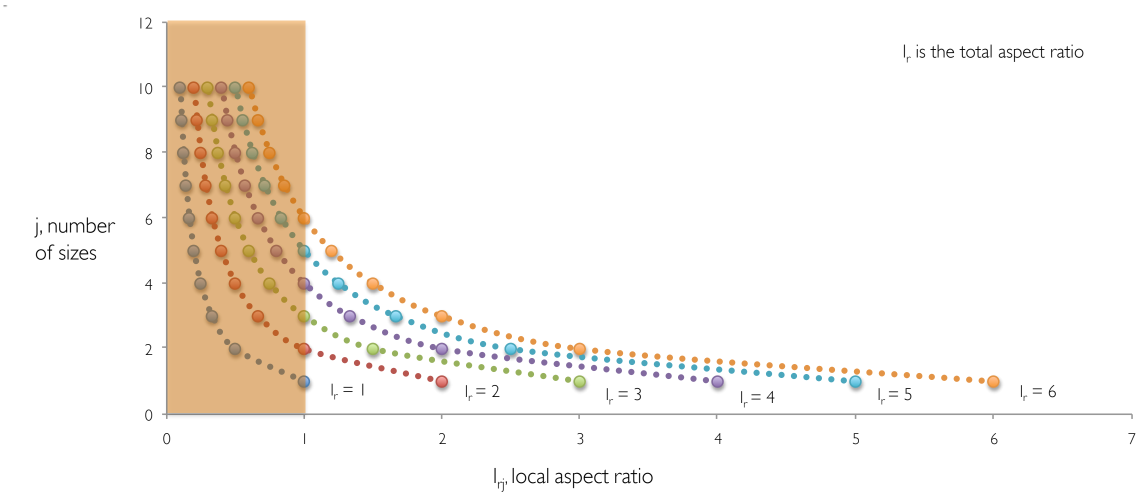
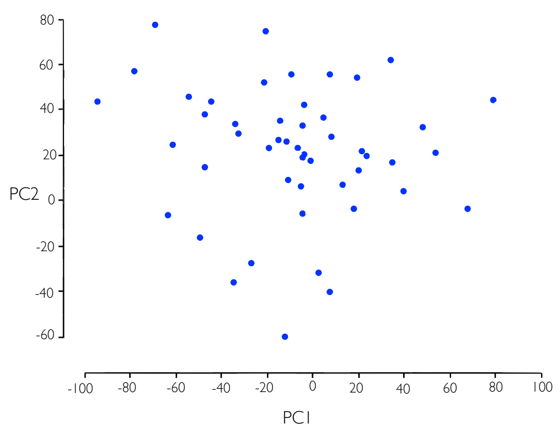
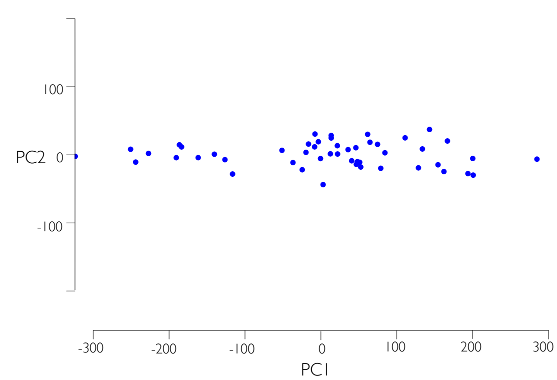


Figure 3.1: Schematic relationship between the number of sizes to be created and the local aspect ratio of the principal components as the ratio of the variance contained in the two principal components increases.



(a) Variance contained in the first two principal components when l_r is close to $1:0$



(b) Variance contained in the first two principal components when l_r is close to $5:0$

Figure 3.2: Plots demonstrating the different scenarios that arise due to a difference in the ratio of the variances contained in the PCs.

3.1 Proposed method

The following method utilizes principal components analysis to determine sizing and adjustability required in a product family to maximize human accommodation.

3.1.1 Identify the design parameters:

A multitude of decisions have to be made while designing a product, many of them related to strength, texture, color, weight, etc. For the purpose of simplicity only the spatial aspects of the design are considered in this work. Therefore, the design parameters will be the various dimensions of a product that need to be determined.

3.1.2 Identify the related anthropometric variables:

Once the dimensional parameters have been identified, they are mapped to the related anthropometric variables. For example, if the height of a seat has to be designed, then the related anthropometry will be "seated popliteal height". The related anthropometry is identified, and the data about these body measures are extracted in the next step.

3.1.3 Select or create a target user population:

The mapping of the design variables to the related anthropometry is possible only if the anthropometric specifications are available. In case the data are not available, anthropometry will have to be generated by using techniques such as population models, hybrid models, or PCA and regression [18, 34]. Once the required body dimensions are obtained, a separate $(m \times n)$ matrix (anthropometry matrix), is created. This matrix contains information about n anthropometric variables for m individuals (real or virtual).

3.1.4 Compute the principal components:

The anthropometry matrix is transformed using PCA to reorient the data in the orthonormal directions (principal components). Typically, the anthropometric data is highly correlated; this implies that the first principal component will account for a much higher amount of variability than the second principal component and so on. The first principal component identifies the direction of maximum variability in the data, and therefore the target population is divided into pools based on this principal component. The individuals belonging to a particular pool exhibit similar physical attributes. If the design requirement demands a greater amount of precision, then the designer can consider a larger amount of variability and select a larger number of PCs to create these pools; conversely, if the demands on precision are lower, then a fewer number of PCs can be selected.

3.1.5 Inspect the loadings on the principal components:

This step ascertains the subsets of anthropometric variables that drive a specific principal component. The PCs that account for a larger amount of variability will indicate the need for sizing, whereas the ones that contain a lesser amount of variability are used to guide the adjustability within the sizes. This mapping essentially establishes the relationship between PCs and the design parameters. It determines the design parameters governed by PCs that contribute towards scaling and the design parameters that contribute towards adjustability. Thus, the scaling and adjustability decisions for the different pools can be made.

3.1.6 Create the product platform:

Establishing a product platform is the most crucial step in designing a product family. Once the loadings have been identified, a domain mapping matrix [13] is used to highlight the common components among the different sizes. These common components can then be grouped together to create a product platform allowing further product development to be carried out with relative ease.

3.1.7 Calculate the final accommodation obtained:

The accommodation offered by the product family after designing in the PC space is calculated.

Steps 1-3 are basic and can be implemented easily. Steps 4 and 5 apply the results of PCA in a new way. The results of PCA are used to determine the components that are to be scaled and those that are to be made adjustable. This method of creating product families can allow for higher levels of accommodation to be achieved. Step 6 involves implementation of the domain mapping matrix and has been explained in Section 2.1 . Step 7 is widely used in DfHV [17]. The rest of the chapter describes steps 4 and 5, which constitute a new application of PCA.

3.2 Principal components analysis

As discussed in Section 2.2, PCA reduces dimensionality and expresses the data in new orthonormal bases that account for the highest amount of variability. The example discussed in Section 2.2.1 to demonstrate the ability of PCA to compress the dimensionality of a problem is revisited to explain Steps 4 and 5.

Ten variables were extracted from the ANSUR database [21] for men, and a separate 1774×10 matrix was created. The ten variables were:

1. biacromial breadth
2. bideltoid breadth
3. buttock popliteal length
4. chest height
5. seated eye height
6. seated hip breadth
7. overhead reach
8. seated popliteal height
9. sitting height
10. stature

PCA is applied to these ten variables to get the first few principal components that account for a large proportion of variability in the whole data set. As seen in Figure 2.2, the first three principal components contain more than 95% of the variation in the data, and the first two principal components contain more than 90% of the variation in the data. To achieve dimensional optimization, either multiple sizes are created or adjustability is provided to certain parameters of the product. Typically, if the amount of variability within the target population is large, then multiple sizes are created instead of allocating a large amount of adjustability. Adjustability is allocated within a particular size to provide continuous accommodation to the users of that size [17]. In a product family, sizing is generally achieved through the scaling of components to help minimize the distinctiveness [41]. Therefore, the first principal component that accounts for a large amount of variation in the data will guide the decisions related to scaling in the product family, and the second and third principal components will guide the adjustability within the sizes.

Figure 3.3 shows the principal components space where the first principal component is represented by the vertical axis whereas the second and third principal components are represented by the horizontal axis. It can clearly be observed that the first principal component is most suitable for scaling since it has the largest variance. In order to achieve optimal sizing or scaling, 95% of the individuals from the anthropometry matrix are divided into three pools depending on their first principal component value. The individuals at the tails of first PC (those with first PC values less than the 2.5^{th} percentile and the ones with first PC values greater than 97.5^{th} percentile) are not included in these pools since the accommodation goal is set at 95%. Multivariate analysis is performed on these pools to determine the final values of the design parameters [20, 24, 44].

Step 5 is concerned with inspecting the relationship between the principal components and the original anthropometry. Table 3.1 shows the loadings on the first three principal components, and Table 3.2 shows the loadings on the rest of the principal components. Since only 95% of the variability in the data is considered, further analysis can be based on the first three principal components (see Table 3.1). Using Table 3.1, the loadings on the principal components can be inspected, and the subsets of the anthropometric variables can be identified. These subsets govern decisions related to scaling or adjustability of the design parameters of the product. The final decision will be based upon two factors: a) the fraction of variability that a principal component contains and b) the anthropometry that loads the principal component the most.

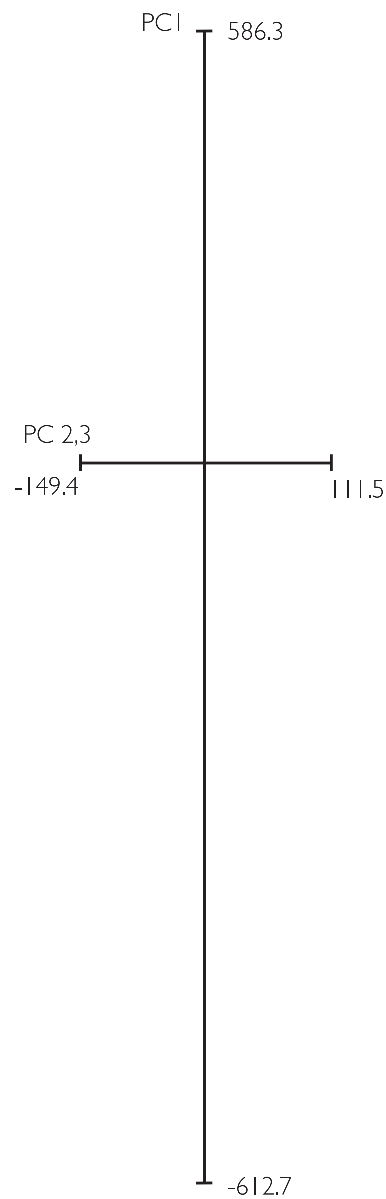


Figure 3.3: First principal component will be used for scaling, whereas the second and third principal components combined will be used to decide adjustability. It can be seen that the variance of the first principal component is much larger than the variance of the second and third principal component combined.

Table 3.1: Loadings on the first three principal components, these PCs will be used for design analysis since they contain 96% of the variability in the data. The first principal component will be used for scaling while the second and third principal components will be used to provide adjustability.

anthropometry	PC1	PC2	PC3
stature	-0.479	0.166	0.143
seated eye height	-0.168	0.589	0.156
seated hip breadth		0.185	-0.576
seated popliteal height	-0.159	-0.185	
biacromial breadth			-0.263
buttock popliteal length	-0.156	-0.207	-0.159
sitting height	-0.176	0.617	0.147
overhead reach	-0.700	-0.307	
bideltoid breadth		0.151	-0.682
chest height	-0.394	-0.106	0.160

Table 3.2: Loadings on the principal components which will not be considered for the design analysis, these PCs only contain about 5% of the variability in the data.

anthropometry	PC4	PC5	PC6	PC7	PC8	PC9	PC10
stature	-0.332	-0.121	0.288	0.356	-0.300	0.478	-0.264
seated eye height	0.126			-0.176	0.118	-0.459	-0.570
seated hip breadth	-0.291	0.565	-0.161	0.350	0.272		
seated popliteal height		-0.190		0.582	-0.224	-0.685	0.174
biacromial breadth	0.260	-0.555	0.256	0.259	0.635		
buttock popliteal length	-0.328	0.117	0.735	-0.384		-0.271	0.138
sitting height							0.740
overhead reach	0.569	0.257		-0.104			
bideltoid breadth		-0.413	-0.163	-0.256	-0.488		
chest height	-0.526	-0.258	-0.496	-0.295	0.350		

The first principal component, which accounts for the maximum variability in the data, is driven by measures related to length in this example. Therefore, the design parameters that can be mapped to the anthropometry that are most influential on PC1 (i.e., design parameters corresponding to stature, overhead reach, and chest height) can be scaled or sized. The bases of this sizing will be the pools created in Step 4. The design parameters corresponding to the anthropometry that affect PC2 and PC3 the most will be provided with a range of adjustability. The anthropometry that load these PCs the most are seated eye height, sitting height, seated hip breadth, and bideltoid breadth. Therefore, the designer could allocate adjustability to the product parameters that are related to these variables. If the primary scaling step does not yield the required accommodation, then the design parameters related to the anthropometry that load the PCs moderately will also be scaled.

The next chapters apply this method to three case studies to help illustrate each step of the method. Three different products are studied, and families of variants are developed for all three products.

CHAPTER 4

CASE STUDY 1: STOOL DESIGN

The product to be designed in this first case study is a stool. Stool was selected in this case study since it has only three design parameters related to anthropometry and thus the proposed method can be demonstrated without any complications. The objective is to create a product family consisting of three sizes of a stool with the help of PCA. The desired level of accommodation is 95%. A step-by-step procedure based on the method outlined in Chapter 3 is described.

4.1 Design procedure based on the proposed method

4.1.1 Identify the design parameters

The dimensions to be decided are seat width, pan depth, and seat height. These design parameters are illustrated in Figure 4.1.

4.1.2 Identify the related anthropometric variables

It can be seen in Figure 4.2 that the anthropometric measures related to the stool's design parameters are: buttock popliteal length, popliteal height, and seated hip breadth. An illustration of these measures can be seen in Figure 4.2.

4.1.3 Select or create a target user population

Due to the selection of the ANSUR database [21], the target population for this case study is limited to U.S. military males. The ANSUR database [21] was selected since it is freely available and contains data related to a wide range of anthropometry. This also eliminated the need for creating a virtual population. The selected database is not the most recent,

Figure 4.1: Design parameters for a stool : pan depth, seat width and seat height. The image has been taken from Konteaki Furniture webpage[1].

but it has accurate records measured with precision; therefore, it will serve the purpose of demonstrating the method.

4.1.4 Compute the principal components

The values of the related anthropometric measures are extracted into a 1774×3 matrix. These measures are transformed into principal components. Table 4.1 displays the results. It can be seen that the proportional variance of the first PC is 61.9% and that of the second PC is 32.3%; together they explain 94.3% of the variability present in the original data. The target user population (ANSUR males [21]) is divided into three pools based on the first PC. Users belonging to a particular pool have relatively similar anthropometry. In the following steps, three designs are created to cater to the users in these pools.

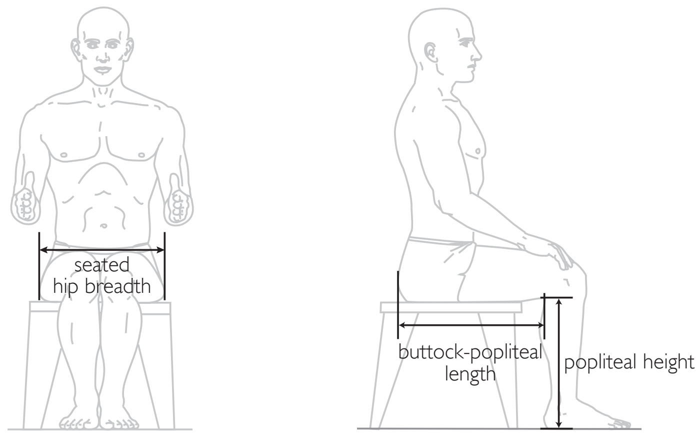


Figure 4.2: Anthropometric measurements related to the design parameters for a stool : buttock popliteal length corresponding to pan depth, popliteal height corresponding to seat height, seated hip breadth corresponding to seat width.

4.1.5 Inspect the loadings on the principal components

The anthropometric measures that load PC1 will be the deciding factors for the scaling or sizing of the product and those that load PC2 will determine the adjustability needed. Table 4.2 shows the loadings on the principal components. Inspection of the loadings tells us which anthropometric measure drives the various principal components. For example, PC1 is driven by seated hip breadth contrasted against buttock-popliteal length and popliteal height. This implies that the variability explained by PC1 corresponds to wide-short people and narrow-tall people. All three measures load PC1 substantially (see Table 4.2). Therefore, buttock-popliteal length, popliteal height, and seated hip breadth will contribute towards scaling. None of the original variables load PC2 substantially; therefore, adjustability will not be allocated to any of the design parameters governed by these anthropometric measures.

Table 4.1: Relative importance of the Principal Components obtained after performing PCA on the anthropometry related to stool design.

	PC1	PC2	PC3
standard deviation	40.48	29.24	12.35
proportional variance	0.6192	0.3231	0.05765
cumulative proportion	0.6192	0.9423	1

4.1.6 Create the product platform

Buttock-popliteal length governs pan depth. The depth of the pan should not exceed the buttock popliteal length of the small people occupying the seat. A deeper seat pan will make contact with the rear of the user's knee joint [37]. Therefore, the pan depth should be less than the smallest value of the buttock-popliteal length. Meanwhile, popliteal height governs the seat height. Even people with short popliteal height should be able to sit in the chair with their feet touching the ground [37]. Therefore, the three different sizes will each have seat heights less than the smallest popliteal heights in their respective pool. Seat widths will be selected based on seated hip breadth; the seat width should be greater than the largest seated hip breadth in a pool so that even the person with the widest hip breadth can be accommodated. Following this procedure, three designs (numbered 1, 2, and 3) were generated. The range of values for each design parameter for the three different sizes is listed in Table 4.3.

In order to create an optimal product family it is necessary to know which components should be kept common and which ones should be distinct. The analysis so far has provided the dimensions of the various design parameters. These dimensions will help to decide the sizes of the various components and to select the components that can be common across the variants with the help of a domain mapping matrix [13]. Decisions taken as a result of this analysis can also help in saving the manufacturing material and cost.

The base seat height is 398 mm for "design # 1", 388 mm for "design # 2" and 373 mm for "design # 3". The four legs of the stool could have modular parts to allow for extension into higher sizes in order to save on material costs. Similarly, the component with a rectangular cross-section (438 $\times$ 416 mm) could be kept common throughout all the

Table 4.2: Loadings on the principal components for stool design.

anthropometry	PC1	PC2	PC3
buttock popliteal length	-0.633	0.254	0.731
popliteal height sitting	-0.733	-0.237	-0.588
seated hip breadth	0.938	-0.346	

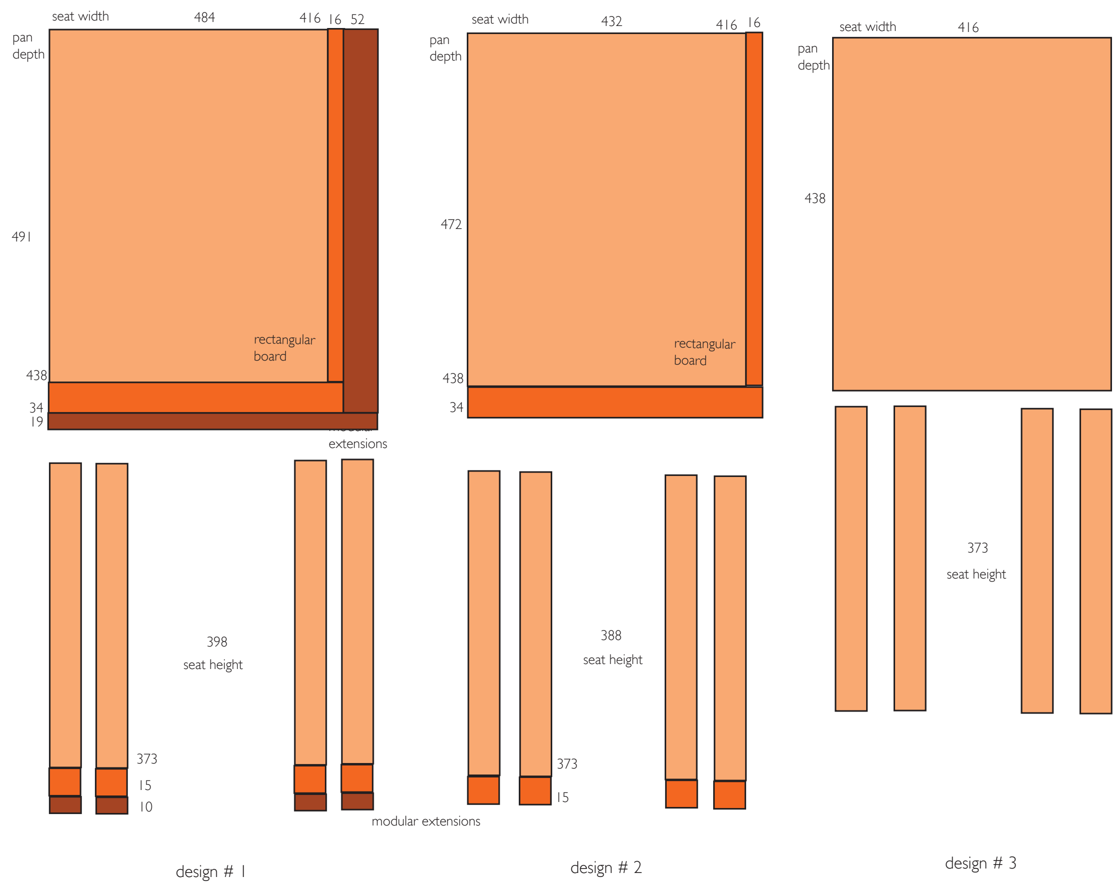


Figure 4.3: This figure shows the components of a product family of stools. The base components are the $438mm \times 416mm$ rectangular board and the cylindrical rod with length $373mm$. The extensions are added to these components to increase the size of the product. The lightest color corresponds to the parts common through out the family and the darkest shade is for the parts unique to only one size.

sizes and modular extensions could be added to increase the pan depth and seat width as shown in the Figure 4.3. For design # 2 a 438 × 16 mm plank can be added to increase the seat width, and a 34 × 432 mm modular extension can be provided to increase pan depth. For design # 1 a 472 × 52 mm modular plank can be added to increase the seat width, and

Table 4.3: Final values of the design parameters for the stool product family.

design	seat height	pan depth	seat width
1	398	491	484
2	388	472	432
3	373	438	416

a 19×484 mm modular extension can be provided to increase pan depth to an existing and extended design # 2 base. Figure 4.3 shows the components of the product family.

The domain mapping matrix (see Table 4.4) relates the components of the product to the different product sizes and helps to establish a product platform. It can be seen that the components common to all the variants of the stool are the four rods of length 373 mm and the rectangular board with dimensions of 438×416 mm. The extensions for design # 1 are the only unique components in the product family since these parts are used only in design # 1.

4.1.7 Calculate the final accommodation obtained

PCA was used to create the three subgroups of the target population and to determine the final values of the design parameters, thereby facilitating the creation of the product platform. The three subgroups had the same number of individuals. Each size was subjected to a virtual fit with the target population specific to its size and achieved a near perfect accommodation; in summary, the product family as a whole will successfully provide 95% accommodation to its target users.

Although this product family achieves the target accommodation level, manufacturers may not find offering a product family of stools profitable. A stool that fits the whole target user population may not be considered imperative, whereas it is very important that a work chair which is occupied by the user for extended periods of time, accommodates all its users.

Table 4.4: Domain mapping matrix for the stool product family.

component/ size	3	2	1
four rods - length 373 mm	X	X	X
four modular rods - length 15 mm		X	X
four modular rods - length 10 mm			X
rectangular board - 438X416 mm	X	X	X
modular extension 438X16 mm for seat width		X	X
modular extension - 34X432 mm for pan depth		X	X
modular extension - 472X52 mm for seat width			X
modular extension - 19X484 mm for pan depth			X

CHAPTER 5

CASE STUDY 2: CHAIR DESIGN

This case study considers a much larger number of design parameters and thus highlights the advantages of principal components analysis. The aim in this case study is to find the spatial dimensions of three sizes of a chair and to allocate adjustability wherever required to ensure maximum accommodation, and to develop a product platform based on these dimensions to create an optimal product family. Typically, chair design concentrates on the fit, support, and feel parameters of the seat [37]. The feel and the support parameters of the seat depend on the pressure distribution and the posture of a person. This example will focus only on the fit parameters of the seat because of the close relation between the fit parameters and anthropometry.

5.1 Design procedure based on the proposed method

5.1.1 Identification the design parameters and related anthropometric measures for the target user population

This section deals with the initial steps (Steps 1—3) of the proposed method. The fit or design parameters considered in this case study are listed in Figure 5.1. The anthropometric measurements corresponding to the fit parameters are listed in Table 5.1 and have been illustrated in Figure 5.2. Some measures needed for this study were not recorded directly in the ANSUR database [21], but it is possible to obtain those measures by performing simple arithmetic operations on the available measures. For example, the anthropometric measure related to armrest length is calculated by subtracting the hand length from the forearm-hand length. Consequently, for each individual in the ANSUR database [21], both forearm-hand length and hand length were extracted, and the new

Figure 5.1: Design parameters for a chair. The image has been taken from Herman Miller webpage [2].

measure related to armrest length for PCA was generated. In addition, both the seat width and the backrest width at the bottom are governed by the seated hip breadth.

5.1.2 Compute the principal components

The selected anthropometric measures were transformed into principal components; the results are displayed in Table 5.2. The first five PCs contain 95.32% of variability in the data, and therefore the anthropometric measures related to these PCs will be used to scale the components for each size offered in the product family and to allocate the adjustability. A majority of the variance (51.72%) is explained by the first PC; also the first two PCs together contain 70.63% of the variability in the data, and therefore these two PCs will be used for sizing and PCs 3-5 will be used for allocating adjustability. PC1 will be used to create subgroups within the target population along the direction of maximum variability. Moreover, the weight of each measure will be determined in conjunction with the loading on the principal component and the amount of variability contained in the principal component.

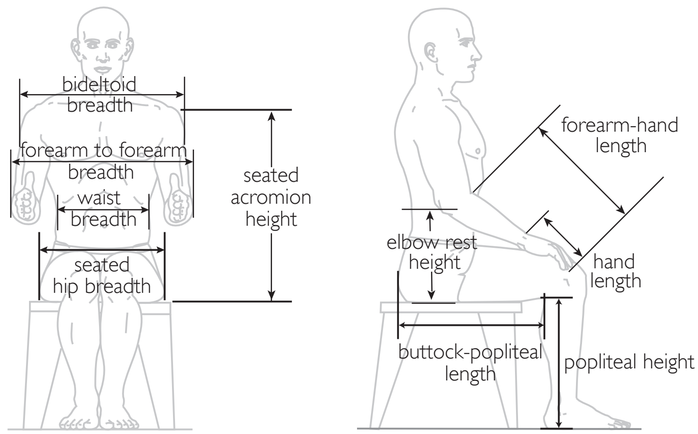


Figure 5.2: Anthropometric measures related to chair design.

5.1.3 Inspect the loadings on the principal components

It can be seen in Table 5.4 that the anthropometric measures which load PC1 significantly are related to breadth (seated hip breadth, bideltoid breadth, forearm to forearm breadth, and waist breadth) and the ones that load PC2 most significantly are related to length (popliteal height, buttock popliteal length, elbow rest height, and armrest length). These anthropometric measures will be used to guide scaling decisions. This leads to the conclusion that all the measures except for armrest length will be scaled for different sizes. This implies that the basic armrest length will be the same throughout the sizes. PCs 3-5 together explain 24.69% of the variability in the data; the anthropometric measures that drive these PCs will be used to allocate adjustability (see Table 5.5). Popliteal height,

Table 5.1: The anthropometric measures corresponding to the fit parameters for chair design.

fit parameter	anthropometric measurement
arm width	forearm to forearm breadth
top backrest width	bideltoid breadth
backrest height	seated acromion height
mid backrest width	waist breadth
bottom backrest width	seated hip breadth
seat width	seated hip breadth
pan depth	buttock popliteal length
seat height	popliteal height
armrest length	forearm-hand length ¬ hand length
armrest height	elbow rest height

elbow rest height, seated acromion height, and forearm to forearm breadth have the highest weight on these principal components; therefore, adjustability will be provided to the design parameters corresponding to these anthropometric measures.

Table 5.2: Percentage of variance contained in each principal component. The PCs calculated by performing PCA on the anthropometry related to chair design.

principal component #	proportional variance	cumulative proportion
1	0.5172	0.5172
2	0.1891	0.7063
3	0.1657	0.872
4	0.0595	0.9315
5	0.0217	0.9532
6	0.0178	0.971
7	0.0142	0.9852
8	0.0080	0.9932
9	0.0065	0.9997

Table 5.3: Loadings on the principal components for chair design. These loadings were obtained after applying PCA to the anthropometric variables related to chair design. This table shows the loadings on all the principal components, but only the first five principal components will be used for further analysis since they contain 95.32% of the variability in the data.

anthropometry	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
seated hip breadth	-0.347			-0.535		-0.137	0.727	-0.205	
popliteal height	-0.114	0.540	0.288	0.205	0.301	0.454		-0.510	-0.118
buttock popliteal length	-0.199	0.568	0.164		-0.605	-0.418	-0.252		
bideltoid breadth	-0.375		-0.150		0.637	-0.599	-0.235		
elbow rest height	-0.172	-0.495	0.463	0.171	-0.155			-0.180	-0.646
armrest length		0.317	0.101		0.199	0.109	0.267	0.766	-0.406
seated acromion height	-0.287	-0.141	0.651	0.177				0.235	0.620
forearm to forearm breadth	-0.637		-0.467	-0.477	-0.262	0.233	0.108		
waist breadth	-0.402			-0.608		0.410	-0.518	0.130	

Table 5.4: Loadings on the first two principal components, the anthropometric measures which load these principal components the most will be used for sizing.

anthropometry	PC1	PC2
seated hip breadth	**-0.347**	
popliteal height	-0.114	0.540
buttock popliteal length	-0.199	0.568
bideltoid breadth	**-0.375**	
elbow rest height	-0.172	-0.495
armrest length		0.317
seated acromion height	-0.287	-0.141
forearm to forearm breadth	**-0.637**	
waist breadth	**-0.402**	

Even though the weight of each measure is determined in conjunction with its influence on the PC, and the amount of variability contained in the PC, it is still in the hands of the designer to decide the cut-off or the threshold value. Therefore, three different product families were created to offer varying levels of scaling. These product families were subjected to a virtual fit analysis, and the accommodation achieved by each was compared along with the tentative cost of building each product family. The number of design parameters scaled differentiated one product family from another. Since the weight of each measure was calculated in conjunction with the loading on the principal component and variance of that PC, the decision to scale the parameter related to that measure remained subjective. In the first product family only the pan depth, arm width, and mid backrest width were scaled. Adjustability was provided to seat height, armrest height, backrest height, and arm width. In the second product family, bottom backrest width, seat width, top backrest width, and armrest height were also scaled. In the third product family, the backrest height and the seat height were scaled too. Table 5.6 shows the components that were scaled or made adjustable in the different product families. The table also compares the cost of development (H being the highest and L being the lowest cost of development) for these product families and the corresponding accommodation provided.

Table 5.5: Loadings on the principal components which govern adjustability related to chair design.

anthropometry	PC3	PC4	PC5
seated hip breadth		-0.535	
popliteal height	0.288	0.205	0.301
buttock popliteal length	0.164		-0.605
bideltoid breadth	-0.150		0.637
elbow rest height	0.463	0.171	-0.155
armrest length	0.101		0.199
seated acromion height	0.651	0.177	
forearm to forearm breadth	-0.467	-0.477	-0.262
waist breadth		-0.608	

5.1.4 Product platform and accommodation obtained

All three product families catered to the same subgroups, which were obtained by trifurcating the target population based on the first PC. The three variants within these product families were subjected to a virtual fit analysis. This virtual fit analysis was performed with the pool of users specific to the variant. Summation of the accommodation provided by each variant within a product family yielded the total accommodation provided by that product family. The total accommodation provided by the product families developed was 94.04% , 93.76% and 93.59%, respectively. The third product family achieved the least accommodation, but most of the parameters in

Table 5.6: Different product families developed due to the subjectivity of the method.

Size	**1**	**2**	**3**
Components	**Sizing and/or Adjustability**	**Sizing and/or Adjustability**	**Sizing and/or Adjustability**
bottom backrest width		S	S
seat width		S	S
seat height	A	A	S and A
pan depth	S and A	S and A	S
top backrest width	A	S	S
armrest height	A	S and A	S and A
armrest length			
backrest height	A	A	S and A
arm width	S and A	S and A	S and A
mid backrest width	S	S	S
cost	H	M	L
accommodation	94.04%	93.76%	93.59%

Table 5.7: Final values of the design parameters for the chair product family.

design	1	2	3
bottom backrest width	458	436	484
seat width	458	436	484
seat height	418-499	402-478	374-456
pan depth	456	454	431
top backrest width	593	552	563
armrest height	140-311	143-299	148-310
armrest length	289	289	289
backrest height	533-682	525-660	512-650
arm width	443-725	434-663	406-674
mid backrest width	461	405	404

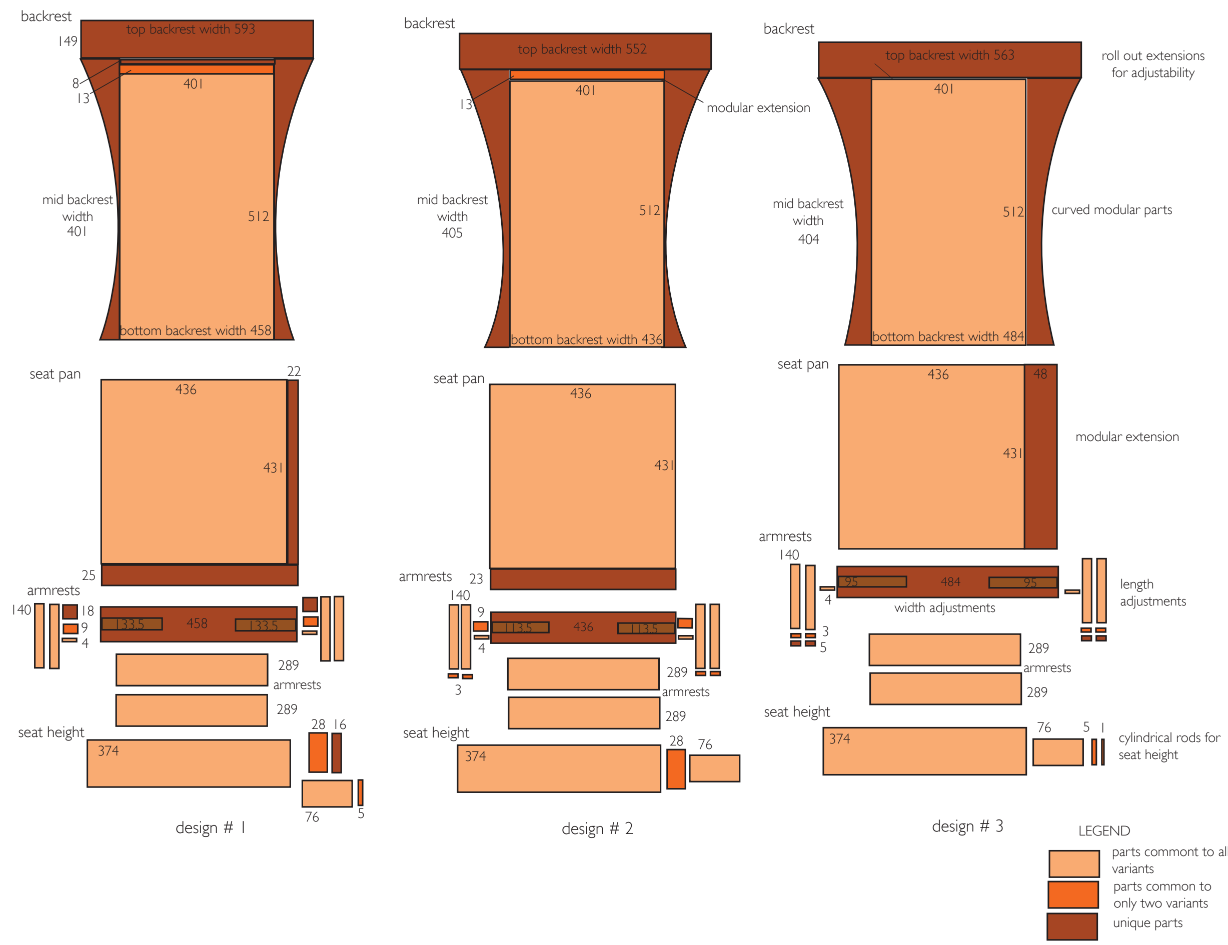


Figure 5.3: This figure shows the components of a family of chairs. The figure shows the various subparts of the backrest, the seat pan, the armrests, and the cylindrical rods for the seat height. The parts common to all the products in the family are the lightest in color, and the unique parts are the darkest in color.

this product family were scaled, thereby creating savings in terms of the material costs. Therefore, the product family developed in the third attempt could be more profitable. This product family is discussed in detail, and a product platform is established.

The range of values for each fit parameter for the three sizes of the chair has been listed in Table 5.7. The product family for the chairs consists of three different products catering to the three subgroups created on the basis of the first principal component. Each product consists of the product platform and additional parts unique to that size. Each size has four subgroups of components related to the backrest, the seat pan, the armrest, and the cylindrical rods for seat height as illustrated in Figure 5.3.

Figure 5.3 and Table 5.8 help in establishing a product platform. It can be seen that the parts common throughout all the sizes are: two cylindrical rods of different diameters that are nested into each other, one of length 374 mm with a larger diameter and the other of length 76 mm with a smaller diameter; two armrests of length 289 mm each; vertical attachments for armrest height adjustment— four rods (two on each side) of length 140 mm that are nested into each other, since the lowest armrest height required is 140 mm; and two rods of length 4 mm for further adjustability. The rectangular board for seat pan 436 mm wide and 431 mm deep will also be common through all the sizes, as will the rectangular board for back rest with a height of 512 mm and a width of 401mm. The details of the unique components are listed in Table 5.8 and illustrated in the Figure 5.3.

Table 5.8: Domain mapping matrix for the chair product family.

component/ size	1	2	3
outer cylindrical rod - length 374 mm	X	X	X
outer cylindrical rod - length 28 mm	X	X	
outer cylindrical rod - length 16 mm	X		
inner cylindrical rod - length 76 mm	X	X	X
inner cylindrical rod - length 5 mm	X		X
inner cylindrical rod - length 1 mm			X
rectangular board - 431X436 mm	X	X	X
L shaped modular extension to make a 456 X 458 mm seat pan	X		
modular extension 431X48 mm for seat width			X
modular extension 23X436 mm for pan depth		X	
two armrests - length 289 mm	X	X	X
width adjustment for armrest 458- 725 mm	X		
width adjustment for armrest 436-663 mm		X	
width adjustment for armrest 484 - 674 mm			X
four vertical attachments (rods) for armrest height adjustment 140 mm	X	X	X
four vertical attachments (rods) for armrest height adjustment 3 mm		X	X
four vertical attachments (rods) for armrest height adjustment 5 mm			X
two vertical attachments (rods) for armrest height adjustment 4 mm	X	X	X
two vertical attachments (rods) for armrest height adjustment 9 mm	X	X	
two vertical attachments (rods) for armrest height adjustment 18 mm	X		
rectangular board 512 X 401 mm for backrest	X	X	X
roll out extension for backrest height 149 X 593 mm	X		
roll out extension for backrest height 135 X 552 mm		X	
roll out extension for backrest height 138 X 563 mm			X
rectangular board 13 X 401 mm modular extension for backrest height	X	X	
rectangular board 8 X 401 mm roll out extension for backrest height	X		
two curved boards with top width 96 mm	X		
two curved boards with top width 75.5 mm		X	
two curved boards with top width 81 mm			X

CHAPTER 6

CASE STUDY 3: SCOOTER DESIGN

The two previous case studies involve examples related to seating. This case study concentrates on a non-seating example—the kick scooter. Kick scooters or push-scooters are human powered vehicles that have a platform or a deck on which the rider stands. They are propelled by the rider pushing with one foot. The deck typically has a front wheel and a back wheel; the front wheel is attached to a handle and is used for steering.

Scooters are widely used by children as toys, but an increase in the popularity of scooters amongst adults for utility riding purposes has been noticed recently. The development of the folding version of the scooter by Wim Ouboter [4] made it easier to carry the scooter in a car or in public transport systems and has therefore contributed to the increase in their popularity.

Figure 6.1 shows the modern scooter used for utility purposes. The folded configuration of the scooter can be seen in the figure as well. The aim in this case study is to determine the dimensions of these design parameters for a product family of scooters suitable for adult usage.

6.1 Design procedure based on the proposed method

6.1.1 Identification of the design parameters, related anthropometry and selection of the arget user population

The initial steps of the proposed methodology are discussed in this section. The design parameters related to anthropometry considered in this case study are: deck width, deck length, handlebar width, and T-rod height. Figure 6.1 illustrates the design parameters that are considered in this case study.

Figure 6.1: Design parameters for a scooter : deck length, deck width, T-rod height, and handlebar width. Image courtesy : www.xootr.com[3].

The anthropometric measures related to the design parameters will be: horizontal foot breadth for deck width, foot length for deck length, biacromial breadth for handlebar width, and acromial height and acromion-radiale length for the T-rod height [27]. These five measures are extracted from the ANSUR [21] database, and elbow height is calculated using the following equation:

$$Elbow\ Height = Acromial\ Height - Acromion.Radiale\ Length \tag{6.1}$$

6.1.2 Compute the principal components

These measures are then transformed into principal components. Table 6.1 shows the variance contained within each principal component, and Table 6.2 shows the anthropometric measures that load each principal component.

The first principal component contains 86.83% (see Table 6.1) of the variability in the data; therefore, the anthropometric measures that load the first component

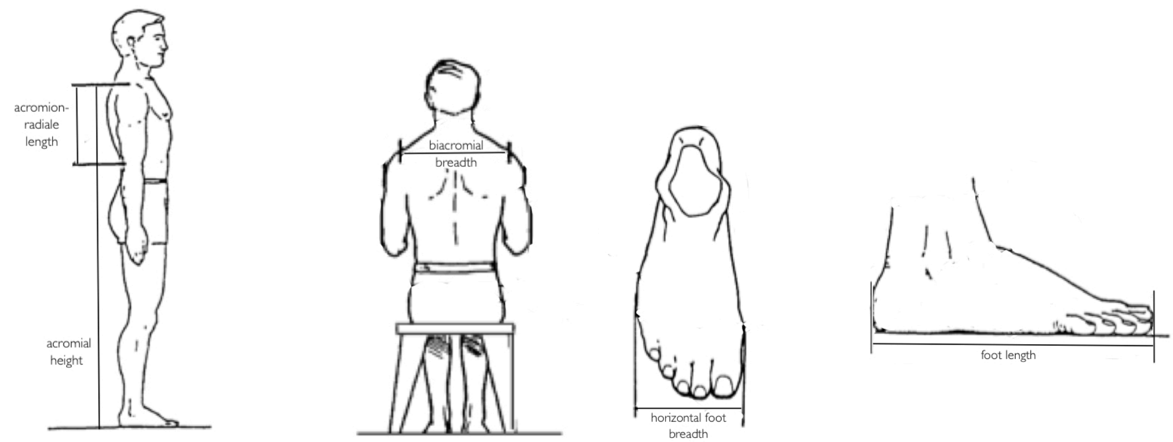


Figure 6.2: Anthropometric measures related to the scooter design are : acromial height, acromion-radilae length, biacromial breadth, horizontal foot breadth and foot length. Elbow height is calculated from the acromial height and acromion-radiale length as : $Elbow\ Length = Acromial\ Height - Acromion.Radiale\ Length.$

guide the design decisions related to the scaling of the components. The second principal component contains 9.56% (see Table 6.1) of the variability in the data, and the anthropometric measures with the maximum loading on it guide decisions related to allocating adjustability.

Table 6.1: Percentage of variance contained in each principal component obtained after performing PCA on the anthropometry related to scooter design. Cumulatively, the first two principal components explain over 95% of the variability in the data , therefore only these components will be used in the further analysis.

principal component #	proportional variance	cumulative proportion
1	0.8683	0.8683
2	0.0956	0.9639
3	0.0302	0.9941
4	0.0057	0.9998

Table 6.2: Loadings on the principal components for scooter design. These loadings were obtained after applying PCA to the the anthropometric variables related to scooter design. This table shows the loadings on all four principal components but only the first principal component will be used for sizing and the second principal component will be used for allocating adjustability.

anthropometry	PC1	PC2	PC3	PC4
elbow height	0.970	0.195	0.147	
foot length	0.180	-0.199	-0.937	-0.225
foot breadth		-0.208	0.974	
biacromial breadth	0.156	-0.958	0.240	

6.1.3 Inspect the loadings on the principal components

The design parameter related to the anthropometric measures with the maximum loading on the first principal component is scaled so that accommodation can be increased by offering different sizes. Elbow height loads the first principal component the most (see Table 6.2); therefore, the T-rod length is the differentiating factor amongst the various sizes offered. Results in Table 6.2 suggest that adjustability should be provided for the handlebar width.

6.1.4 Product platform and accommodation obtained

The final values of the design parameters have been listed in Table 6.3, and the product platform can be seen in Figure 6.3. The maximum T-rod height for the three different sizes will vary. Scooters available nowadays are foldable. Therefore, the T-rod will consist of two rods, one nested into another so that the T-rod is able to shrink to the length of the deck for proper overlap after folding to facilitate easy storage. This provides adjustability. The maximum T-rod height in each pool is kept smaller than the elbow height of the tallest person in that pool. The handlebar width will be kept adjustable for users with a biacromial breadth of 330 mm to 451 mm. This implies that soft grips that are 230 mm apart will be provided on a rod 550 mm in length so that the handlebar can be comfortably used riders. The maximum foot breadth is 122 mm; in order to facilitate placing both feet side by side, the deck width should be at least twice the breadth of the foot. There should be a considerable margin for shoes, etc. on the deck. The deck length is the length of the platform excluding the length of the material that surrounds the wheels. It should be at least twice the length of the foot so that the rider is able to place their feet in a desirable configuration on the deck.

Table 6.3: Final values of the design parameters for the scooter product family.

design	1	2	3
T-rod height	1088	1125	1200
handlebar width	550	550	550
deck width	300	300	300
deck length	650	650	650

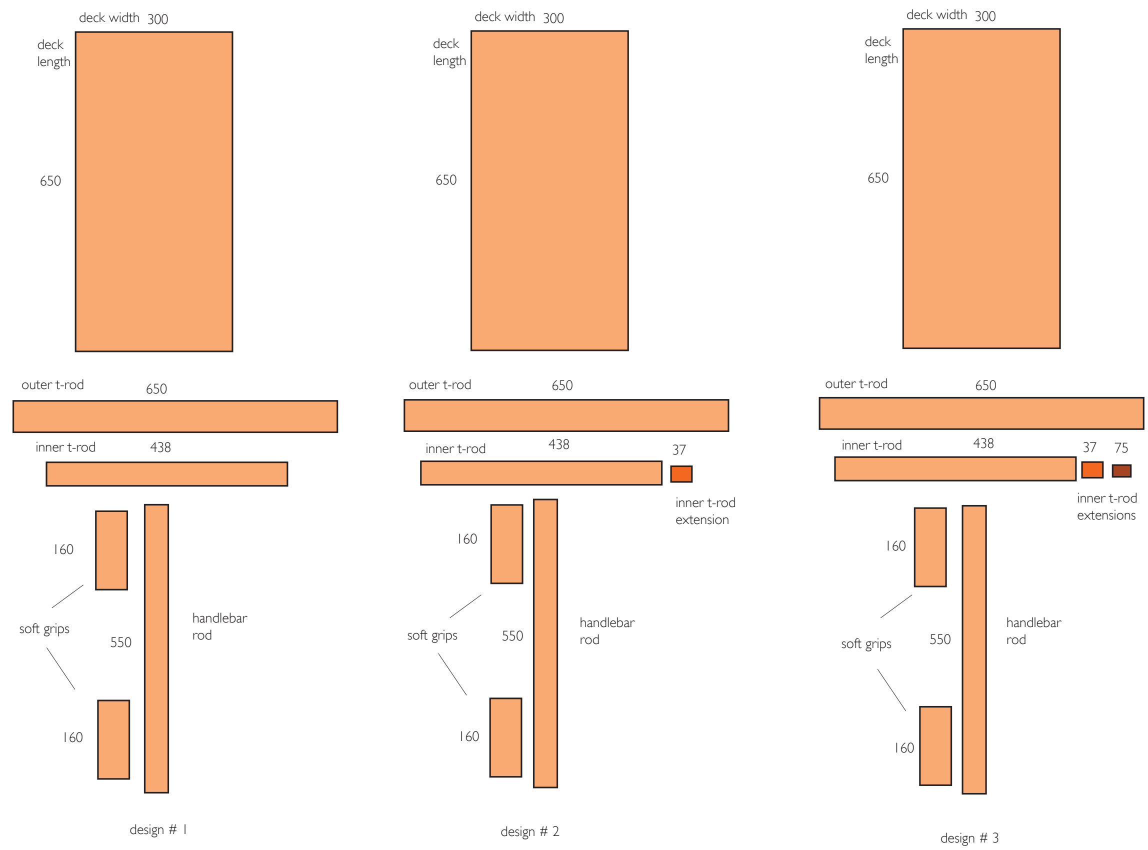


Figure 6.3: This figure shows the components of a product family of scooters.

Table 6.4 shows the domain mapping matrix for this product family. It can be seen that this product family has a very high level of commonality and extremely low diversity. The variant termed design # 1 is essentially the product platform; design # 2 and design # 3 are derived simply by adding an extension for the T-rod.

Table 6.4: Domain mapping matrix for the scooter product family.

component/ size	1	2	3
rectangular board - 300X650 mm	X	X	X
outer T-rod - length 650 mm	X	X	X
inner T-rod - length 438 mm	X	X	X
inner T-rod - length 37 mm modular extension		X	X
inner T-rod - length 75 mm modular extension			X
two soft grips for handle bar - length 160 mm	X	X	X
handlebar rod - length 550 mm	X	X	X

The variant products in this product family were each subjected to a virtual fit analysis performed on the target user pool. These three pools were obtained after dividing the target user population (ANSUR [21]) into three sections based on the first PC obtained earlier in the analysis. The results obtained in the individual fitting trials were added to extract the overall accommodation provided by this family of products. This product family accommodates 94.54% users of the target population.

CHAPTER 7

DISCUSSION AND CONCLUSIONS

The aim of this research was to develop a strategy that employs principal components analysis (PCA) to aid in the estimation of the levels of commonality and distinctiveness required in a family of products intended for human use. The method utilizes the ability of PCA to identify the underlying variability in a target user population to create sub-groups within the population. It helps to ascertain the number of sizes that need to be created and the adjustability that needs to be allocated in the variants of the product to be offered so that accommodation is maximized and cost is minimized.

In Section 2.2, PCA was explained in detail and supported by two examples. These examples illustrated the ability of PCA to reduce the dimensionality of a dataset and to identify the variables which contribute towards augmenting the variance. It touched upon product platform, commonality, distinctiveness, and design tools like domain mapping matrix. This section also explored the various applications of PCA in DfHV. Section 2.1 provided an outline of product family design.

A method to determine the sizing and adjustability required in product families to achieve desired human accommodation was proposed in Chapter 3. It integrates the advantages of principal components analysis and product family design tools like the domain mapping matrix. The method consists of the following seven steps:

1. Identify the design parameters.
2. Identify the related anthropometric variables.
3. Select or create a target user population.
4. Compute the principal components.

5. Inspect the loadings on the principal components.

6. Create the product platform.

7. Calculate the final accommodation.

Steps 4-6 integrate the advantages of PCA and the domain mapping matrix. The principal components computed in Step 4 group people with similar anthropometry. Step 5 ascertains the design parameters that are to be sized and/or made adjustable. The basis of the decisions made in Step 5 is the amount of influence the corresponding anthropometric variables have on the principal components. Step 6 utilizes the domain mapping matrix to deduce the common components and to estimate the commonality and distinctiveness required in the product family, and thereby create a product platform.

Three case studies demonstrated the application of the proposed method in DfHV problems. The three products considered for in the case studies were: a stool (see Figure 4.1), a chair (see Figure 5.1), and a scooter (see Figure 6.1). The stool and the chair case studies highlighted the difference in the need for sizing and adjustability in a product related to seating whereas the scooter case study dealt with a product that lays more emphasis on body parts related to length measures as opposed to width measures.

It was observed that no adjustability had to be provided to any design parameter of the stool. The three differently sized stools were able to achieve the required accommodation. One variant of the product family coincided with the product platform itself, and only one variant had components that were unique (see Figure 4.3). This product family resulted in a near perfect accommodation and promised to be profitable owing to the high amount of commonality.

The case study in Chapter 5 considered a higher number of variables than the stool case study. Therefore, it harnessed the power of PCA more efficiently than the stool case study, which had only three design variables. Three different product families were developed upon following the method since the amount of variability to be considered depended on the designer. The accommodation level achieved by all three product families was compared along with the development time and cost for that product family. The product family which resolved this trade-off the best was discussed in detail. It was observed that armrest length was the only design parameter that did not require any sizing or adjustability. The product family can be seen in Figure 5.3. Virtual fitting trials on this product family indicated an expected accommodation of 93.59%.

The only variation in the product family of scooters was due to the length of the T-rod (see Figure 6.3). In order to be accepted by the market, the scooter has to be foldable. In order to satisfy this requirement, the T-rod was made adjustable. This adjustability might increase user satisfaction, although the accommodation level even without the incorporation of this adjustability would remain the same.

In the case study related to stool design, the ratio of the variance contained in PC1 and PC2 is 2 : 1. This implies that PC2 contains enough variance which must be addressed by providing adjustability to the anthropometric measures that influence PC2. However, the anthropometric measures that load PC1 are the same as the ones that load PC2; therefore, their contribution to the variability was accommodated by offering different sizes. Hence, no adjustability had to be provided for this case study.

In the case study involving chair design, the first PC explained 51.72% of the variance and the second PC explained 18.91% of the variance. Therefore, in order to design with precision and accommodate the required amount of variability (at least 95%) more than two PCs had to be considered in this case study. A total of five PCs were considered to explain 95.32% of the variance in the data. Design parameters related to the anthropometric measures that influence PCs 1-2 were scaled and those related to the anthropometric measures that load PCs 3-5 were made adjustable. This ensured that the target accommodation levels are reached.

There was a wide disparity between the variance explained by PC1 and that explained by PC2 in the case study related to scooter design. The nature of the design of the product eliminated the need for different components for handle bar width. Therefore, incorporating this adjustability did not make a difference in the levels of commonality and distinctiveness. This design had adjustability for the T-rod due to the restriction of foldability. Interestingly, this design is similar to the design that would be created if the shortcoming (as explained in Section 7.2) of this example is addressed.

7.1 Research contributions

The primary contribution of this thesis research is that it partitions the target user population into pools of people with similar body types using PCA and conducts design in PCA space. The proposed method developed determines sizing and adjustability based on PCA loadings. The identification of the direction of maximum variance provides the designer with a basis to sort individuals within a target population into pools and design accordingly. Variants of products that specifically cater to these niche segments are then developed and thus achieve better accommodation since the subjects in the pools are more homogenous.

This division not only facilitates the integration of product family concepts into the design but makes sure that product family developed is profitable. Since the basis of this division is the first principal component, most of the variability present in the data is accounted for. At the same time, the individuals constituting a particular pool do not vary much. Therefore, each variant is created to fit a small portion of the population and considers the variability present in that portion only. This allows for creation of variants with optimal levels of distinctiveness and commonality, thereby reducing the material cost. As a whole, the product family spans the variability of all the users in the target population.

The method proposed in this thesis could be particularly beneficial in designs that involve the consideration of a large number of anthropometric variables. The use of PCA can reduce the complications associated with a multivariate DfHV problem by compressing the dimensionality of the datasets and recognizing the anthropometric variables that contribute significantly to the variance of the dataset.

7.2 Limitations and future work

The biggest limitation of this work arises from the fact that the method developed is not completely objective. Step 5 in the method consists of inspecting the loadings on the principal components. The anthropometric variables that influence the PC which explains the maximum variance in the data are scaled, and those that affect the PC which explains the next highest amount of variance in the data are made adjustable. Some anthropometric variables have a higher value of factor loading for a PC than the others; deciding the threshold value for these factor loadings is subjective and depends on the designer using the method.

Therefore, the method proposed is likely to yield differing solutions to the same DfHV problem when used by different designers. It can also create different solutions when the threshold value of the factor loadings is altered by the same designer (as demonstrated in Chapter 5). The three different product families were compared with each other in terms of the accommodation provided and the product development cost. The assumption made in this comparison (i.e., the product development cost will primarily be dependent upon the material cost) could be a source of error.

The proposed method expects the second PC to be dominant enough to guide the adjustability decisions for the product being considered. However, in the case that there is a wide disparity between the first and the second eigenvalue (e.g., if the ratio of the variance explained by PC1 to the ratio of the variance explained by PC2 is greater than 8:1) , this hypothesis is not true. In that case, PCA can be applied to the individual pools created on the basis of the first PC to find the direction of maximum variability. Adjustability can then be provided to anthropometry measures that influence the first PC obtained after performing PCA on the subgroups. This PC is likely to be oriented in the same direction as the PC used to create the subgroups. The similarity will lead to allocation of adjustability to the same measures that influence the initial PC that has a large amount of variance. It is a predictable outcome since both sizing and adjustability within those sizes will have to be provided to accommodate a large range of variability.

Future work can consider other factors that influence product development time and cost in detail. This will aid in resolving the aforementioned trade-off. Exploring the factors that influence development time and cost more thoroughly will minimize the impact of a designer's subjectivity on the final design. Another decision hinging on the designer's preference will be the amount of variability to be considered in the data. The amount of variability considered will directly affect the precision of the resulting design. However, this decision must be subjective to avoid unnecessary and high development cost.

Future work can also address another shortcoming of this research, which was the use of anthropometry of males in the ANSUR database [21] for analysis. This database was used to demonstrate the proposed method as it was easily accessible. Future research efforts could use a virtually created user target population [34] specific to a demographic group of interest, or specific to a region for the analysis and produce readily applicable results.

Different product families comprising of three variants of the products considered in each case study were developed. Future work could explore the change that occurs in levels of commonality and distinctiveness when the number of variants is changed.

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